Measuring and Forecasting Emergency Department Crowding in Real Time

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Study objective: We quantified the potential for monitoring current and near-future emergency department (ED) crowding by using 4 measures: the Emergency Department Work Index (EDWIN), the National Emergency Department Overcrowding Scale (NEDOCS), the Demand Value of the Real-time Emergency Analysis of Demand Indicators (READI), and the Work Score.

Methods: We calculated the 4 measures at 10-minute intervals during an 8-week study period (June 21, 2006, to August 16, 2006). Ambulance diversion status was the outcome variable for crowding, and occupancy level was the performance baseline measure. We evaluated discriminatory power for current crowding by the area under the receiver operating characteristic curve (AUC). To assess forecasting power, we applied activity monitoring operating characteristic curves, which measure the timeliness of early warnings at various false alarm rates.

Results: We recorded 7,948 observations during the study period. The ED was on ambulance diversion during 30% of the observations. The AUC was 0.81 for the EDWIN, 0.88 for the NEDOCS, 0.65 for the READI Demand Value, 0.90 for the Work Score, and 0.90 for occupancy level. In the activity monitoring operating characteristic analysis, only the occupancy level provided more than an hour of advance warning (median 1 hour 7 minutes) before crowding, with 1 false alarm per week.

Conclusion: The EDWIN, the NEDOCS, and the Work Score monitor current ED crowding with high discriminatory power, although none of them exceeded the performance of occupancy level across the range of operating points. None of the measures provided substantial advance warning before crowding at low rates of false alarms. [Ann Emerg Med. 2007;49:747-755.]

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INTRODUCTION

Background

Emergency department (ED) crowding is recognized to be a major, international concern that affects patients and providers.[1-10] A recent report from the Institute of Medicine noted that the increasing strain caused by crowding is creating a deficit in quality of emergency care.[11] Crowding has been associated with reduced access to emergency medical services,[12-15] delays in care for cardiac patients,[16-18] increased patient mortality,[19-22] extended patient transport time,[23,24] inadequate pain management,[25] violence of angry patients against staff,[26] increased costs of patient care,[27] and decreased physician job satisfaction.[28]

Importance

As suggested by the principle that you cannot manage what you cannot measure, the lack of a universal metric for ED crowding impedes efforts to alleviate the problem.[29,30] In an effort to address this, mathematical formulas have been proposed in the peer-reviewed literature to quantify crowding: the Emergency Department Work Index (EDWIN), the National Emergency Department Overcrowding Scale (NEDOCS), the Demand Value of the Real-time Emergency Analysis of Demand Indicators (READI), and the Work Score.[31-35] These 4 measures use simple operational variables to assess the present state of crowding in an ED.

There have been mixed reports in the literature about the usefulness of these measures to assess ED crowding.[31-41] Previous validation efforts have often used subjective assessments of crowding by physicians and nurses as the dependent variable.[31,32,34,37,39,41] The measures were intended for continuous monitoring of ED operations[31-35]; however, only the Work Score has been integrated with a clinical

Editor's Capsule Summary

What is already known on this topic

In the absence of an accepted definition of emergency department (ED) crowding, multiple scores have been proposed to measure this phenomenon.

What question this study addressed

How 5 metrics for measuring current and impending ED crowding fared in predicting ambulance diversion status during an 8-week period in a single adult ED.

What this study adds to our knowledge

All measures performed reasonably well at measuring crowding in real time, but none outperformed the simplest measure, ED occupancy level. None of the measures was particularly useful as a short-term warning system for future crowding.

How this might change clinical practice

This study will not change clinical practice but suggests that ED occupancy, the simplest metric for measuring ED crowding, performs just as well as more complex methods.

information system.[35] Furthermore, the measures have the potential to serve as an early warning system for crowding.[31,35] This capability, however, has not yet been established for any of the measures.

Goals of This Investigation

The objective of this study was to assess the usefulness of the EDWIN, the NEDOCS, the READI Demand Value, and the Work Score as monitoring instruments of ED crowding. To achieve this goal, we addressed 3 related questions. First, is it feasible to evaluate the measures in real time? Second, how accurately do the measures reflect present crowding? Finally, can the measures reliably forecast the future state of crowding?

MATERIALS AND METHODS

Study Design

This was a prospective validation of 4 ED crowding measures during an 8-week period (June 21, 2006, to August 16, 2006). The study did not involve any direct patient contact, and the local institutional review board approved the study by expedited review.

Setting

The validation took place in the adult ED of a tertiary care, academic medical center with a Level I trauma service. The adult ED provides care for more than 45,000 patients annually. It contains 41 licensed beds, 4 of which are trauma beds. In addition, 4 fast-track beds are available for low-acuity patients from 11 AM to 11 PM, and 8 dedicated rooms are available for psychiatric patients. The ED staff was kept unaware of the study to avoid a potential source of bias. The validation site was independent of the development site for all measures considered.

Methods of Measurement

The EDWIN, the NEDOCS, the READI Demand Value, and the Work Score were calculated to assess the degree of crowding.[31-35] All 4 of these measures output a continuous variable, where a higher value denotes a greater degree of crowding.

The EDWIN[31] was calculated using the following formula:

$$\text{EDWIN} = \sum n_i t_i / \left(N_a \times \left(B_t - P_{board}\right)\right)$$

where n_i=number of nonboarding patients in triage category i; t_i=reversed triage category i, where 5 denotes the sickest patients and 1 denotes the least sick patients; N_a=number of attending physicians on duty; B_t=number of licensed treatment beds in the ED; and P_{board}=number of boarding patients.

The NEDOCS[32] was calculated using the following formula:

$$\text{NEDOCS} = \left(P_{bed}/B_t\right) \times 85.8 + \left(P_{admit}/B_h\right) \times 600 \\ + W_{time} \times 5.64 + A_{time} \times 0.93 + R_n \times 13.4 - 20$$

where P_{bed}=number of patients in licensed beds and overflow locations, such as hallway beds or chairs, B_t=number of licensed treatment beds, P_{admit}=number of admitted patients, B_h=number of hospital beds, W_{time}=waiting time for the last patient put into bed, A_{time}=longest time since registration among boarding patients, and R_n=number of respirators in use, maximum of 2. The respirator variable (R_n) did not generalize to the study setting, because patients ill enough to require mechanical ventilation are stabilized and transferred immediately to a critical care unit. As a surrogate, the number of trauma beds was used in place of the number of respirators.

The Demand Value of the READI score[33,34] was calculated using the following formulas:

$$DV = \left(BR + PR\right) \times AR$$

$$BR = \left(P_{total} + A_{pred} - D_{pred}\right)/B_t$$

$$AR = \sum n_i t_i / P_{triage}$$

$$PR = A_{hour} / \sum PPH$$

where DV=Demand Value, BR=bed ratio, AR=acuity ratio, PR=provider ratio, P_{total}=number of ED patients, A_{pred}=number of predicted arrivals, D_{pred}=number of predicted departures, B_t=number of licensed treatment beds, n_i=number of patients in triage category i, t_i=reversed triage category i, P_{triage}=number of patients in the ED with an assigned triage category, A_{hour}=number of arrivals in the past hour, and PPH=average patients seen per hour for each attending physician and resident on duty. The predicted number of arrivals (A_{pred}) and departures (D_{pred}) for each hour of the day was calculated using 9 months of ED data (September 1, 2005, to June 1, 2006). The original READI instrument used a 4-level triage system, so the 5-level Emergency Severity Index was condensed into 4 categories by combining the 2 least severe acuity

levels.[42] The number of patients treated per hour was calculated for residents at each level of training and for attending physicians who treated patients without a resident, using 9 months of ED data (September 1, 2005, to June 1, 2006).

The Work Score[35] was calculated using the following formula:

$$\text{Work Score} = 3.23 \times P_{wait}/B_t + 0.097 \times \sum n_i t_i / N_n + 10.92 \times P_{board}/B_t$$

where P_{wait}=number of waiting patients, Bt=number of licensed treatment beds, n_i=number of patients under evaluation in triage category i, t_i=triage category i, N_n=number of nurses on duty, and P_{board}=number of boarding patients.

The ED occupancy level was used as a control measure for baseline comparison. The occupancy level was calculated using the following formula:

$$\text{Occupancy level} = 100 \times P_{bed}/B_t$$

where P_{bed}=number of patients in licensed beds and overflow locations, such as hallway beds or chairs; and B_t=number of licensed treatment beds.

Under extreme operating conditions, the original published formulas for the EDWIN and the acuity ratio of the READI score could generate mathematic errors. If the number of boarding patients in the ED matched or exceeded the number of licensed treatment beds, the denominator of the EDWIN would become zero or negative. If there were no patients in the ED with an assigned triage category, the denominator of the acuity ratio would become zero. However, these conditions have never been approached in the study setting, so no changes to compensate for this were deemed necessary for the present study.

Data Collection and Processing

To enable real-time monitoring of ED operations, a computer program was developed using Matlab (version 7.1, Mathworks, Natick, MA; available at http://www.mathworks.com) and integrated with the ED information systems. At 10-minute intervals, the program queried the information systems for the data required to evaluate the 4 crowding measures and the occupancy level. The resulting values were recorded in a research database.

Outcome Measures

Ambulance diversion status was used as the outcome measure for crowding. Policy at our hospital allows for ambulance diversion when any of the following criteria apply and are not expected to be remedied within 1 hour: (1) all critical care beds in the ED are occupied, patients are occupying hallway spaces, and at least 10 patients are waiting; (2) an acuity level exists that places additional patients at risk; or (3) all monitored beds within the ED are full. A committee reviews the appropriateness of all diversion episodes monthly. The hospital's aeromedical service, which is responsible for maintaining diversion records, provided log files for the study period.

Primary Data Analysis

The ability of each crowding measure to discriminate current ambulance diversion status was analyzed using receiver operating characteristic (ROC) curves.[43] An ROC curve plots sensitivity against (1–specificity) for all possible thresholds in a binary classification task. The area under an ROC curve (AUC) represents the overall discriminatory ability of a test, where a value of 1.0 denotes perfect ability and a value of 0.5 denotes no ability. To reduce the effect of serial correlation on ROC curve estimation, each measure series was down-sampled to an observation frequency of 3 hours. The AUC of each measure was calculated with 95% confidence intervals (CI). Pairwise tests for significant differences of AUC were conducted between each measure and occupancy level.[44] An α level of 0.05/4=0.0125, with the Bonferroni correction for multiple pairwise comparisons, was used for the tests of significance. All ROC analyses were performed with the ROCKIT software package (version 0.9.1, Kurt Rossman Laboratories, Chicago, IL; available at http://xray.bsd.uchicago.edu/krl/roc_soft.htm). The operating characteristics of each measure were calculated by fixing each measure's threshold to achieve 90% sensitivity with respect to ambulance diversion status. At this fixed threshold, each measure's specificity, predictive values, and likelihood ratios were calculated.

The ability of each crowding measure to forecast ambulance diversion status in the near future was analyzed, following the Centers for Disease Control and Prevention framework for evaluating biosurveillance systems.[45] Activity monitoring operating characteristic curves were developed to characterize the performance of early warning systems,[46] and they have been previously applied to the problem of disease outbreak detection.[47,48] An activity monitoring operating characteristic curve plots timeliness scores against false-alarm rates for all possible thresholds in an early warning system. The false-alarm rate is generally normalized per unit time; in the present study, per week. The timeliness score may be interpreted here as the median warning time given before diversion, within a maximum specified window. The window was defined to be 4 hours for this study, and alarms were classified as (1) true alarms if they occurred less than 4 hours before the start of a diversion episode; (2) false alarms if they occurred more than 4 hours before the start of a diversion episode; or (3) redundant alarms if they occurred during a diversion episode. Redundant alarms were not further considered, because they affect neither the timeliness nor the false-alarm rate.

The standard method of generating activity monitoring operating characteristic curves would treat all false alarms as independent events, even when they occurred at consecutive 10-minute intervals.[46] From an ED operational perspective, we considered it more appropriate to treat consecutive alarms as a single, sustained alarm because only the first alarm would trigger an intervention. Thus, the activity monitoring operating characteristic framework was extended for the present study as follows. Each measure series was denoised using cubic spline

Table 1. ED operational variables (June 21, 2006, to August 16, 2006).

Characteristic	No Diversion (n=5,599)	Diversion (n=2,349)
Patient factors		
Registrations in last hour, No.	6 (3–8)	6 (4–9)
Discharges in last hour, No.	5 (3–8)	7 (5–9)
Mean acuity level (Emergency Severity Index)	2.57±0.16	2.57±0.12
Occupancy level, %	78 (61–88)	96 (91–100)
Average length of stay, h	5.4 (3.9–8.3)	8.0 (6.3–9.6)
Waiting patients, No.	1 (0–4)	11 (5–16)
Average waiting time, min	11 (0–31)	84 (52–115)
Boarding patients, No.	9 (4–15)	20 (15–23)
Average boarding time, h	5.7 (2.5–10.2)	10.4 (7.0–12.6)
Provider factors		
Attending physicians on duty, No.	3.0±0.9	3.5±0.7
Residents on duty, No.	4.4±0.5	4.7±0.5
Nurses on duty, No.	13.5±1.8	14.5±1.5
Hospital factors		
Medical-surgical diversion, %	15	26
Critical care diversion, %	4	13

Observations were made at 10-minute intervals during the study period. Descriptions are presented as percentages for discrete variables, mean±SD for normally distributed continuous variables, and median (interquartile range) for skewed variables.

smoothing with the Matlab function *csaps*. A smoothing parameter of 0.99 was applied, where a value of 1.0 represents no smoothing and values below 0.95 resulted in excessive smoothing. Each sequence of consecutive alarms was counted as a single, sustained signal. However, when a trough in the smoothed signal occurred during a sustained false alarm, it was considered to be the beginning of a new false alarm, thus ensuring a monotonic relationship between the false-alarm rate and timeliness. All activity monitoring operating characteristic analyses were performed using Matlab (version 7.1; available at http://www.mathworks.com).

The timeliness of the 4 crowding measures and occupancy level were compared by fixing the threshold such that each measure triggered 1, 2, and 3 false alarms per week, which was considered the maximum number likely to be tolerated by ED personnel. The timeliness before every diversion episode was calculated, and a paired Wilcoxon rank-sum test was used to compare the median difference in timeliness between each measure and occupancy level. The Bonferroni-corrected 95% CIs, equivalent to unadjusted 98.75% CIs, were calculated using R (version 2.3.1; available at http://www.r-project.org).

RESULTS

During the study period, a total of 7,948 10-minute intervals were observed out of 8,064 possible (98.6%). Two incidents of computer system downtime accounted for all of the missed observations. Descriptive statistics for ED operational variables during the study period are listed in Table 1. A total of 37 ambulance diversion episodes occurred during the study period, lasting an average of 11.7 hours per episode. There were no episodes of citywide diversion, such that the ED was forced to end its diversion, during the study period. The ED was on ambulance diversion during 30% of the intervals observed. To illustrate the response of each measure to ED crowding, Figure 1 shows an 8-week time series plot of each crowding measure, superimposed on episodes of ambulance diversion.

Main Results

The ROC curves for the EDWIN, the NEDOCS, the READI Demand Value, the Work Score, and occupancy level are shown in Figure 2. The AUC was 0.81 for the EDWIN (95% CI 0.77 to 0.85), 0.88 for the NEDOCS (95% CI 0.85 to 0.91), 0.65 for the READI Demand Value (95% CI 0.60 to 0.71), 0.90 for the Work Score (95% CI 0.86 to 0.92), and 0.90 for occupancy level (95% CI 0.87 to 0.93). Pairwise tests for differences of AUC showed that occupancy level had greater discriminatory power for crowding than the EDWIN ($P<.001$) and the READI Demand Value ($P<.001$), while the NEDOCS and the Work Score did not differ significantly in discriminatory power from occupancy level ($P=.190$ and $P=.769$, respectively). The operating characteristics for each measure at a fixed sensitivity level of 90% are shown in Table 2.

The activity monitoring operating characteristic curves for the EDWIN, the NEDOCS, the READI Demand Value, the Work Score, and occupancy level are shown in Figure 3. Only the occupancy level provided more than an hour of advance warning (median 1 hour 7 minutes) before crowding at a rate of 1 false alarm per week. Note that the vertical distance between curves in Figure 3 illustrates the difference between medians of timeliness; however, with nonparametric paired data, the median difference shown in Table 3 may provide more reliable comparisons. As assessed by CIs that do not overlap zero, the occupancy level gave more timely warnings of crowding than the EDWIN at rates of 1, 2, and 3 false alarms per week. When the false-alarm rate was fixed at 3 per week, the READI Demand Value gave more timely warnings of crowding than occupancy level. All other pairwise comparisons of median timeliness to occupancy level were not statistically significant.

LIMITATIONS

A potential limitation of our study is the use of ambulance diversion status as a surrogate for crowding. Although a clear, universal definition for ED crowding does not exist, an expert panel considered ambulance diversion status to be a practical, operational definition.[49] It has been used previously as an dependent variable to validate crowding measures.[35,36,40] The justifiability of using ambulance diversion status as an objective surrogate for crowding depends on the rigor of diversion policy at a given institution. As described previously, our institution has specified criteria by which ambulance diversion may be initiated, and regular reviews are conducted to ensure compliance. On these grounds, ambulance diversion status was considered to be the best available reference standard for crowding in this study.

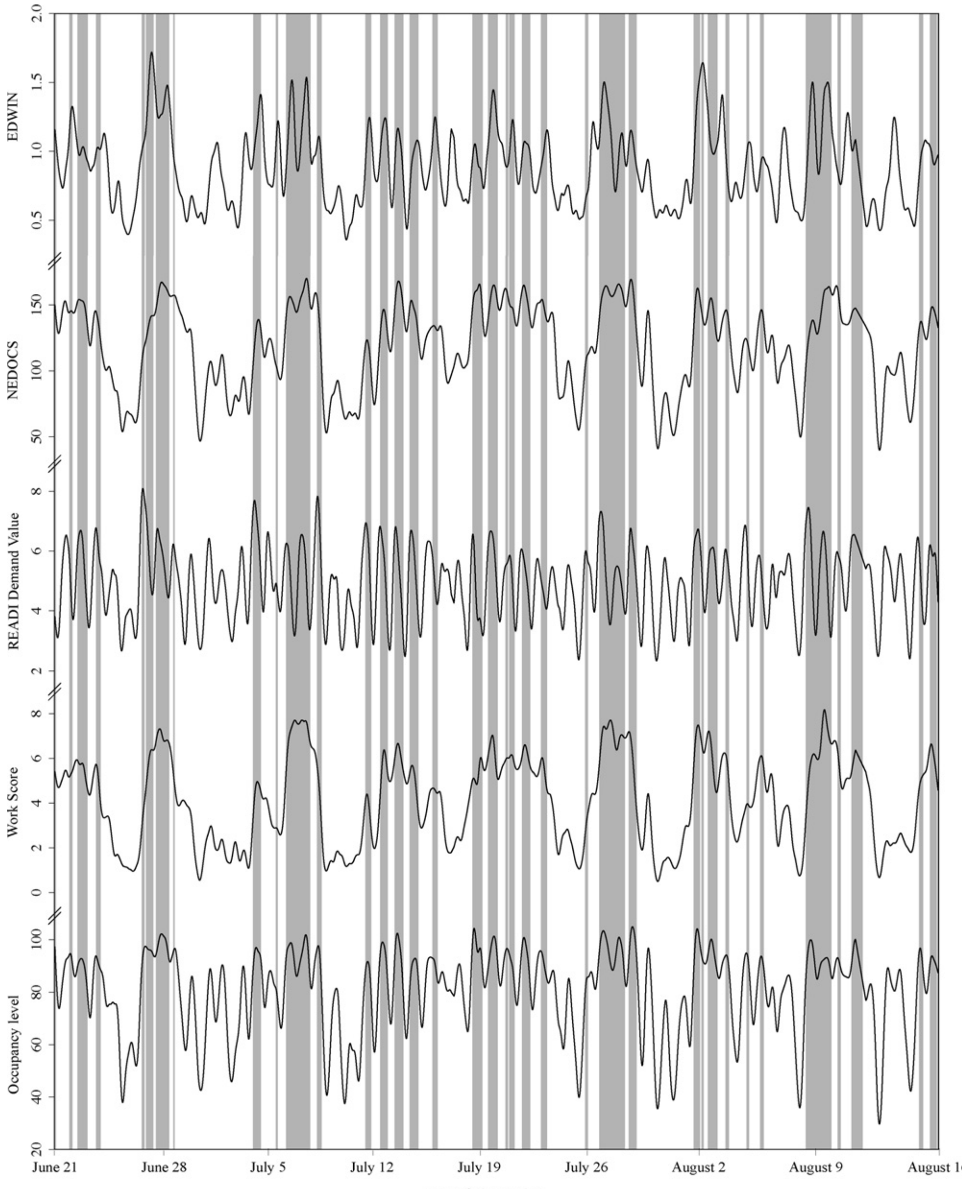

Figure 1. Time series plots of the crowding measures during the study period. The plots shown here are smoothed using cubic splines. Episodes of ambulance diversion are marked by the shaded areas.

A second limitation arises from the fact that the 4 crowding measures—the EDWIN, the NEDOCS, the READI Demand Value, and the Work Score—were originally developed for the purpose of measuring the present state of crowding.[31-35] The creators of the EDWIN and the Work Score discussed the potential use of the measures to forecast near-future crowding, without directly exploring this application.[31,35] Because the creators of the NEDOCS and the READI did not explicitly describe this possibility, we acknowledge that validating these measures as early warning systems by activity monitoring operating characteristic analysis may have exceeded the authors' intentions.[32-34]

Last, the study was conducted at a single academic institution, and further research will be required to determine the generalizability of the findings to other ED settings. However, because this study represents an independent, prospective validation of all 4 crowding measures, some notion of their generalizability may be inferred from the findings.

DISCUSSION

The findings demonstrate that the EDWIN, the NEDOCS, the READI Demand Value, and the Work Score may be evaluated in real time by integration with ED information

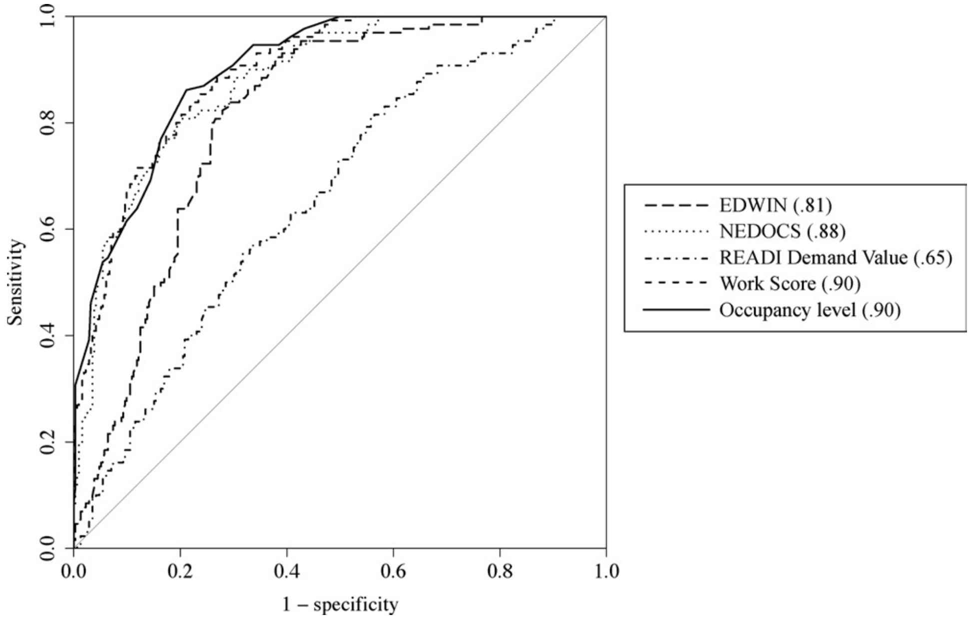

Figure 2. Receiver operating characteristic curves of the crowding measures. The AUC of each measure is shown in parentheses.

Table 2. Operating characteristics at fixed 90% sensitivity.

Measure	Spec, %	PPV, %	NPV, %	LR+	LR−
EDWIN	63	50	94	2.42	0.15
NEDOCS	67	53	94	2.75	0.15
READI Demand Value	32	35	88	1.32	0.32
Work Score	71	56	94	3.09	0.14
Occupancy level	70	56	95	3.05	0.13

LR+, Positive likelihood ratio; *LR−,* negative likelihood ratio; *NPV,* negative predictive value; *PPV,* positive predictive value; *Spec,* specificity.

systems.[31-35] Implementing the 4 measures as monitoring instruments requires the electronic availability of common ED operational variables, such as waiting room count, length of stay, and number of boarding patients.

We examined the ability of the 4 measures to reflect current ED crowding. The ROC curves and operating characteristics demonstrate that the EDWIN, the NEDOCS, and the Work Score all have high discriminatory power for predicting current ambulance diversion status. However, none of the measures performed better than the control measure, occupancy level. The READI Demand Value showed lower discriminatory power, which is consistent with an earlier report that found no significant association between the READI Demand Value and staff assessments of crowding.[34]

We also examined the ability of the 4 crowding measures to forecast near-future ED crowding. According to the activity monitoring operating characteristic curves and the timeliness at fixed false-alarm rates, all measures had difficulty providing much advance notice at low rates of false alarms. None of the available crowding measures clearly exceeded the control measure, occupancy level, in forecasting performance. Although the READI Demand Value showed poor discriminatory power, it performed much better in the activity monitoring operating characteristic analysis. The time series plots in Figure 1 suggest that, although the other measures tend to peak in the middle of diversion episodes, the READI Demand Value appears to peak close to the beginning of diversion episodes, lending credence to its timeliness.

Two points should be noted from the analysis of forecasting power. First, it is insufficient to consider only operating characteristics such as sensitivity, specificity, and discriminatory power when validating an early warning system. Good performance in terms of discriminatory power does not imply timely forecasts, and vice versa. The Centers for Disease Control and Prevention recommended a careful analysis of timeliness when public health monitoring systems are evaluated.[45] Second, the READI Demand Value is the only measure evaluated that predicts near-future operational changes based on historical data. The other 3 measures and occupancy level are all point estimates based on current operating status. It is plausible that the use of historical data to predict near-future patient arrivals and departures explains why the READI Demand Value fares relatively well in forecasting ED crowding.

Occupancy level was intended as a simple baseline measure for comparison in the present study. It was interesting to find that none of the 4 crowding measures clearly exceeded its performance across the range of operating points. This finding is near in spirit to Occam's razor: Roughly paraphrased, one should use the most parsimonious model possible that achieves the intended purpose, since more complex models may be prone to overfitting.

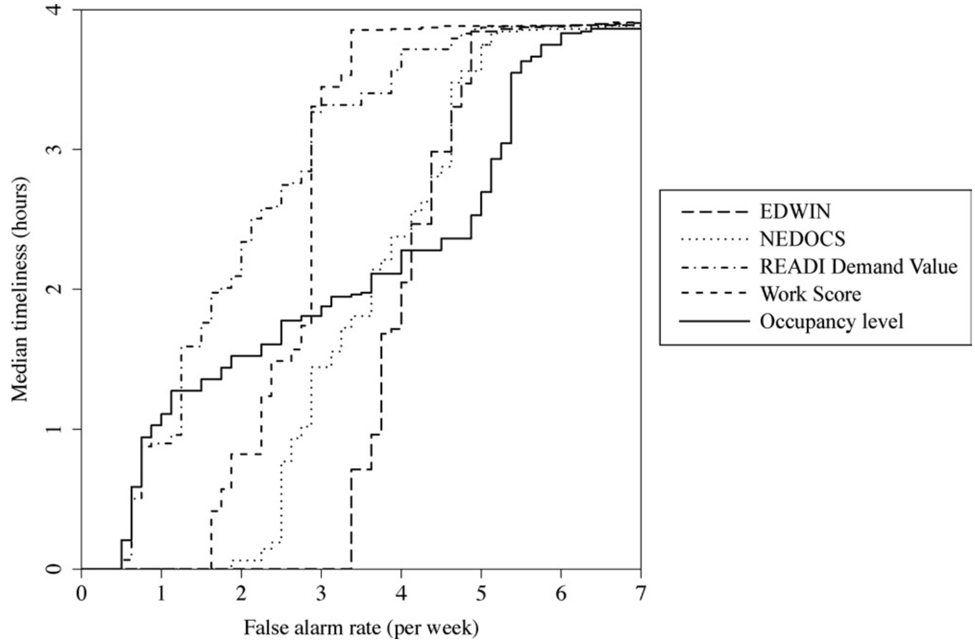

Figure 3. Activity monitoring operating characteristic curves of the crowding measures. A higher value of timeliness denotes a greater amount of warning time before episodes of ambulance diversion.

Table 3. Median difference in timeliness between crowding measures and occupancy level.*

	False-Alarms Rate/week		
Measure	**1**	**2**	**3**
EDWIN	−1:37 (−2:48,−0:09)	−2:06 (−3:20,−0:28)	−2:01 (−2:53,−0:35)
NEDOCS	−1:04 (−2:24,0:19)	−1:06 (−2:26,0:27)	−0:24 (−1:56,0:50)
READI Demand Value	0:04 (−1:16,1:14)	0:43 (−0:50,1:42)	1:16 (0:00,2:05)
Work Score	−1:17 (−2:37,0:13)	−0:20 (−1:49,1:20)	0:02 (−1:32,1:39)

*Differences in timeliness are presented as hours:minutes. A positive value indicates that the measure gave more timely warnings than occupancy level. Lower and upper bounds of the Bonferroni-corrected 95% CI for the median difference are shown in parentheses.

Future efforts to validate ED crowding measures should focus on using objective endpoints to define crowding. Although not all institutions allow for ambulance diversion, researchers at any ED could define a rule involving the occupancy level, waiting room count, or other basic variables as the reference standard. The use of subjective assessment as the sole dependent variable when a crowding measure is validated should be treated cautiously. For example, conflicting reports have been published about the utility of the NEDOCS to measure crowding, which may illustrate the difficulty of replicating findings based on a subjective dependent variable.[32,37,39]

Future research should also focus on improving the forecasting power of crowding measures. The use of historical data to predict changes in the next few hours may allow for substantial improvements in the performance of an early warning system. Advanced modeling techniques such as neural networks, applied specifically for the purpose of forecasting, may result in improved forecasting power.[40] The development of a good forecasting model for ED crowding will pave the way to studying intervention policies, which may allow researchers to identify ways of sustaining health care quality and access in the face of crowding.[50] Other researchers have discussed strategies including the use of reserve physicians and nurses[51] and deferring care of low-acuity patients,[52,53] either of which could be initiated, given a few hours of advance warning before crowding.

In summary, the findings demonstrate the feasibility of implementing 4 measures for real-time monitoring of ED crowding. Occupancy level showed discriminatory power similar to or greater than the 4 other measures for measuring current ED crowding. In terms of timely forecasting, none of the measures showed a clear advantage over occupancy level. These findings suggest new directions for the measurement and management of ED crowding.

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REFERENCES

1. Gallagher EJ, Lynn SG. The etiology of medical gridlock: causes of emergency department overcrowding in New York City. *J Emerg Med*. 1990;8:785-790.
2. Andrulis DP, Kellermann A, Hintz EA, et al. Emergency departments and crowding in United States teaching hospitals. *Ann Emerg Med*. 1991;20:980-986.
3. Derlet RW, Richards JR. Overcrowding in the nation's emergency departments: complex causes and disturbing effects. *Ann Emerg Med*. 2000;35:63-68.
4. Derlet R, Richards J, Kravitz R. Frequent overcrowding in U.S. emergency departments. *Acad Emerg Med*. 2001;8:151-155.
5. Richardson LD, Hwang U. Access to care: a review of the emergency medicine literature. *Acad Emerg Med*. 2001;8:1030-1036.
6. Richardson LD, Asplin BR, Lowe RA. Emergency department crowding as a health policy issue: past development, future directions. *Ann Emerg Med*. 2002;40:388-393.
7. Schneider SM, Gallery ME, Schafermeyer R, et al. Emergency department crowding: a point in time. *Ann Emerg Med*. 2003;42:167-172.
8. Trzeciak S, Rivers EP. Emergency department overcrowding in the United States: an emerging threat to patient safety and public health. *Emerg Med J*. 2003;20:402-405.
9. Agouridakis P, Hatzakis K, Chatzimichali K, et al. Workload and case-mix in a Greek emergency department. *Eur J Emerg Med*. 2004;11:81-85.
10. American Academy of Pediatrics Committee on Pediatric Emergency Medicine. Overcrowding crisis in our nation's emergency departments: is our safety net unraveling? *Pediatrics*. 2004;114:878-888.
11. Committee on the Future of Emergency Care in the United States Health System. *Hospital-Based Emergency Care: At the Breaking Point*. Washington, DC: National Academies Press; 2006.
12. Baker DW, Stevens CD, Brook RH. Patients who leave a public hospital emergency department without being seen by a physician. Causes and consequences. *JAMA*. 1991;266:1085-1090.
13. Polevoi SK, Quinn JV, Kramer NR. Factors associated with patients who leave without being seen. *Acad Emerg Med*. 2005;12:232-236.
14. Fatovich DM, Nagree Y, Sprivulis P. Access block causes emergency department overcrowding and ambulance diversion in Perth, Western Australia. *Emerg Med J*. 2005;22:351-354.
15. Rowe BH, Channan P, Bullard M, et al. Characteristics of patients who leave emergency departments without being seen. *Acad Emerg Med*. 2006;13:848-852.
16. Schull MJ, Vermeulen M, Slaughter G, et al. Emergency department crowding and thrombolysis delays in acute myocardial infarction. *Ann Emerg Med*. 2004;44:577-585.
17. Schull MJ, Morrison LJ, Vermeulen M, et al. Emergency department gridlock and out-of-hospital delays for cardiac patients. *Acad Emerg Med*. 2003;10:709-716.
18. Schull MJ, Morrison LJ, Vermeulen M, et al. Emergency department overcrowding and ambulance transport delays for patients with chest pain. *CMAJ*. 2003;168:277-283.
19. Miro O, Antonio MT, Jimenez S, et al. Decreased health care quality associated with emergency department overcrowding. *Eur J Emerg Med*. 1999;6:105-107.
20. Begley CE, Chang Y, Wood RC, et al. Emergency department diversion and trauma mortality: evidence from Houston, Texas. *J Trauma*. 2004;57:1260-1265.
21. Sprivulis PC, Da Silva JA, Jacobs IG, et al. The association between hospital overcrowding and mortality among patients admitted via Western Australian emergency departments. *Med J Aust*. 2006;184:208-212.
22. Richardson DB. Increase in patient mortality at 10 days associated with emergency department overcrowding. *Med J Aust*. 2006;184:213-216.
23. Redelmeier DA, Blair PJ, Collins WE. No place to unload: a preliminary analysis of the prevalence, risk factors, and consequences of ambulance diversion. *Ann Emerg Med*. 1994;23:43-47.
24. Eckstein M, Chan LS. The effect of emergency department crowding on paramedic ambulance availability. *Ann Emerg Med*. 2004;43:100-105.
25. Hwang U, Richardson LD, Sonuyi TO, et al. The effect of emergency department crowding on the management of pain in older adults with hip fracture. *J Am Geriatr Soc*. 2006;54:270-275.
26. Jenkins MG, Roche LG, McNicholl BP, et al. Violence and verbal abuse against staff in accident and emergency departments: a survey of consultants in the UK and the Republic of Ireland. *J Accid Emerg Med*. 1998;15:262-265.
27. Krochmal P, Riley TA. Increased health care costs associated with ED overcrowding. *Am J Emerg Med*. 1994;12:265-266.
28. Rondeau KV, Francescutti LH. Emergency department overcrowding: the impact of resource scarcity on physician job satisfaction. *J Healthc Manag*. 2005;50:327-340.
29. Hwang U, Concato J. Care in the emergency department: how crowded is overcrowded? *Acad Emerg Med*. 2004;11:1097-1101.
30. Solberg LI, Asplin BR, Weinick RM, et al. Emergency department crowding: consensus development of potential measures. *Ann Emerg Med*. 2003;42:824-834.
31. Bernstein SL, Verghese V, Leung W, et al. Development and validation of a new index to measure emergency department crowding. *Acad Emerg Med*. 2003;10:938-942.
32. Weiss SJ, Derlet R, Arndahl J, et al. Estimating the degree of emergency department overcrowding in academic medical centers: results from the National ED Overcrowding Study (NEDOCS). *Acad Emerg Med*. 2004;11:38-50.
33. Reeder TJ, Garrison HG. When the safety net is unsafe: real-time assessment of the overcrowded emergency department. *Acad Emerg Med*. 2001;8:1070-1074.

34. Reeder TJ, Burleson DL, Garrison HG. The overcrowded emergency department: a comparison of staff perceptions. *Acad Emerg Med*. 2003;10:1059-1064.
35. Epstein SK, Tian L. Development of an emergency department work score to predict ambulance diversion. *Acad Emerg Med*. 2006;13:421-426.
36. McCarthy ML, Aronsky D, Jones I, et al. Validation of the Emergency Department Work Index at six academic emergency departments [abstract]. *Acad Emerg Med*. 2006;13:S28.
37. Weiss SJ, Ernst AA, Nick TG. Comparison of the National Emergency Department Overcrowding Scale and the Emergency Department Work Index for quantifying emergency department crowding. *Acad Emerg Med*. 2006;13:513-518.
38. Weiss SJ, Ernst AA, Derlet R, et al. Relationship between the National ED Overcrowding Scale and the number of patients who leave without being seen in an academic ED. *Am J Emerg Med*. 2005;23:288-294.
39. Raj K, Baker K, Brierley S, et al. National Emergency Department Overcrowding Study tool is not useful in an Australian emergency department. *Emerg Med Australas*. 2006;18:282-288.
40. Hoot NR, Aronsky D. An early warning system for overcrowding in the emergency department. *Proc AMIA Annu Fall Symp*. 2006: 339-343.
41. Jones SS, Allen TL, Flottemesch TJ, et al. An independent evaluation of four quantitative emergency department crowding scales. *Acad Emerg Med*. 2006;13:1204-1211.
42. Wuerz RC, Milne LW, Eitel DR, et al. Reliability and validity of a new five-level triage instrument. *Acad Emerg Med*. 2000;7:236-242.
43. Hanley JA, McNeil BJ. The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology*. 1982; 143:29-36.
44. Metz CE, Herman BA, Roe CA. Statistical comparison of two ROC-curve estimates obtained from partially-paired datasets. *Med Decis Making*. 1998;18:110-121.
45. Buehler JW, Hopkins RS, Overhage JM, et al. Framework for evaluating public health surveillance systems for early detection of outbreaks: recommendations from the CDC Working Group. *MMWR Recomm Rep*. 2004;53:1-11.
46. Fawcett T, Provost F. Activity monitoring: noticing interesting changes in behavior. In: Madigan C, ed. *5th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. New York: ACM Press; 1999:53-62.
47. Mostashari F, Hartman J. Syndromic surveillance: a local perspective. *J Urban Health*. 2003;80:1-7.
48. Wong WK, Moore A, Cooper G, et al. WSARE: what's strange about recent events? *J Urban Health*. 2003;80:66-75.
49. Schull MJ, Slaughter PM, Redelmeier DA. Urban emergency department overcrowding: defining the problem and eliminating misconceptions. *Can J Emerg Med*. 2002;4:76-83.
50. Forster AJ. An agenda for reducing emergency department crowding. *Ann Emerg Med*. 2005;45:479-481.
51. Bucheli B, Martina B. Reduced length of stay in medical emergency department patients: a prospective controlled study on emergency physician staffing. *Eur J Emerg Med*. 2004;11: 29-34.
52. Washington DL, Stevens CD, Shekelle PG, et al. Next-day care for emergency department users with nonacute conditions. A randomized, controlled trial. *Ann Intern Med*. 2002;137:707-714.
53. Kelen GD, Scheulen JJ, Hill PM. Effect of an emergency department managed acute care unit on ED overcrowding and emergency medical services diversion. *Acad Emerg Med*. 2001;8: 1095-1100.

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DIAGNOSIS:

Hemorrhagic pancreatitis. The diagnosis was presumed according to clinical presentation and the presence of the Cullen sign. A lipase of 5,534 U/L and the CT image of the pancreas and surrounding fluid confirmed the diagnosis.[1] The patient was admitted to the medical ICU for aggressive hydration, hemodynamic monitoring, and prophylactic parenteral antibiotics.

Hemorrhagic pancreatitis occurs when pancreatic enzymes extravasate and erode through local vasculature. The high mortality rate is manifested through gastrointestinal bleeding, multiple organ dysfunction, disseminated intravascular coagulation, and infection. Management is largely supportive (hydration, pancreatic rest, electrolyte monitoring).[2]

Cullen[3] first described periumbilical discoloration in ruptured ectopic pregnancy and acute pancreatitis. Turner[4] later described flank discoloration in cases of hemorrhagic pancreatitis. Most recently, helical CT has demonstrated anterior extension of pancreatic enzymes from the gastrohepatic ligament and across the falciform ligament in acute pancreatitis,[5] which causes hemorrhage within the properitoneal fat deep to the umbilicus.

REFERENCES

1. Balthazar EJ, Fisher LA. Hemorrhagic complications of pancreatitis: radiologic evaluation with emphasis on CT imaging. *Pancreatology*. 2001;1:306-313.
2. Nathens AB, Curtis JR, Beale RJ, et al. Management of the critically ill patient with severe acute pancreatitis. *Crit Care Med*. 2004;32:2524-2536.
3. Cullen TS. *Embryology, Anatomy, and Diseases of the Umbilicus Together with Diseases of the Urachus*. Philadelphia, PA: Saunders and London; 1916.
4. Turner GG. Local discoloration of abdominal wall as a sign of acute pancreatitis. *Br J Surg*. 1920;7:394-395.
5. Sugimoto M, Takada T, Yasuda H, et al. MPR-hCT imaging of the pancreatic fluid pathway to Grey-Turner's and Cullen's sign in acute pancreatitis. *Hepatogastroenterology*. 2005;52:1613-1616.